

Edge AI and Federated Learning in Smart City Engineering: A Cross-Domain Review of Architectures, Applications, and Deployment Challenges in Transportation, Environmental, and Building Systems

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Abstract

Edge Artificial Intelligence (Edge AI) and Federated Learning (FL) have emerged as the two dominant methodological trends reshaping how AI and Internet of Things (IoT) systems are deployed across urban engineering domains, yet existing reviews continue to organize the field by application sector rather than by these transversal deployment paradigms. This review addresses the gap through a cross-domain synthesis of Edge AI and FL implementations spanning transportation, environmental, and building engineering, drawing on peer-reviewed literature published between January 2021 and February 2026. A structured search protocol applied across IEEE Xplore, Scopus, ScienceDirect, ACM Digital Library, and Web of Science identified an initial corpus that, after screening against pre-registered inclusion criteria and a PRISMA 2020 selection flow, yielded over 200 studies for inclusion. The review makes four contributions: (1) a transversal taxonomy that classifies smart city AI implementations along axes of computation locality (cloud, fog, edge, on-device) and learning paradigm (centralized, federated, hybrid), exposing methodological convergence patterns invisible in domain-siloed reviews; (2) a five-layer reference architecture explicitly annotated with Edge AI and FL placement decisions; (3) a comparative synthesis of deployment outcomes across more than thirty international case studies, contrasting infrastructure-intensive and resource-constrained settings; and (4) an evidence-based research agenda identifying eight open problems where Edge AI and FL maturity remains insufficient for production-grade urban deployment. The findings indicate that Edge AI delivers consistent latency and energy benefits in transportation and building applications where on-device inference is feasible, while FL is most impactful where data sovereignty, regulatory constraint, or cross-jurisdictional coordination dominate the problem geometry, particularly in environmental monitoring and multi-stakeholder energy systems. Implementation challenges persist in model drift under non-IID urban data, communication efficiency under intermittent connectivity, and the absence of standardized fairness and explainability tooling for distributed urban AI. This work provides actionable guidance for civil engineers, urban planners, technology providers, and policymakers selecting between centralized, edge, and federated deployment strategies for next-generation urban infrastructure.

Keywords: Artificial Intelligence; Internet of Things; Smart Cities; Edge AI; Federated Learning; Privacy-Preserving Machine Learning; Intelligent Transportation Systems; Urban Infrastructure; TinyML; Distributed Learning.

1. Introduction

1.1 Urban engineering challenges in the age of rapid urbanization

The twenty-first century has witnessed an unprecedented acceleration of global urbanization, fundamentally transforming the landscape of human civilization and presenting profound challenges for urban engineering systems. According to the United Nations, approximately 55% of the world's population currently resides in urban regions, with projections indicating this proportion will exceed 68% by 2050.^[1] This rapid urban expansion generates substantial pressure on existing infrastructure systems, including transportation networks, energy grids, water distribution systems, and waste management facilities. Traditional engineering approaches, characterized by reactive maintenance strategies and siloed operational frameworks, have proven inadequate to address the complexity and scale of contemporary urban challenges.^[2] Urban engineering systems face multifaceted challenges that demand innovative technological solutions. Transportation networks in major metropolitan areas experience chronic congestion, with average commuters in developed nations losing approximately 54 hours annually to traffic delays, resulting in significant economic losses and environmental degradation.^[3] Environmental infrastructure struggles with increasing pollution levels, inadequate waste management systems, and inefficient resource utilization. Air quality monitoring in urban centers reveals that over 90% of the global urban population lives in areas where air quality exceeds World Health Organization guidelines.^[4] Building energy consumption accounts for approximately 40% of global energy use and 36% of carbon dioxide emissions, highlighting the critical need for intelligent building management systems.^[5] Water distribution networks suffer from aging infrastructure, with developed nations experiencing water loss rates of 15-30% due to leakage, while developing nations face losses exceeding 40%.^[6] These engineering challenges are further compounded by the dynamic nature of urban systems, characterized by high variability in demand patterns, complex interdependencies between infrastructure components, and the need for real-time adaptive responses to changing conditions. Traditional engineering methodologies, relying primarily on historical data analysis and static optimization models, lack the flexibility and computational capacity to manage such complexity effectively.^[7] Moreover, the increasing frequency of extreme weather events attributable to climate change imposes additional stress on urban infrastructure, necessitating resilient engineering solutions capable of predictive risk assessment and adaptive response mechanisms.^[8]

1.2 Artificial intelligence and IoT as enabling technologies

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has emerged as a transformative paradigm for addressing urban engineering challenges through data-driven decision-making and autonomous system optimization. AI encompasses a broad spectrum of computational techniques, including Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and computer vision, that enable systems to learn from data, recognize patterns, and make intelligent decisions without explicit programming.^[9,10] IoT technology facilitates the deployment of interconnected sensor networks, actuators, and communication devices that enable real-time data collection, monitoring, and control of physical infrastructure systems.^[11] The integration of AI and IoT creates intelligent cyber-physical systems capable of continuous learning, adaptive optimization, and autonomous decision-making. ML algorithms, including supervised learning techniques such as Support Vector Machines (SVM), Random Forests, and Neural Networks, enable predictive modeling of complex urban phenomena, from traffic flow patterns to energy consumption forecasts.^[12] DL architectures, particularly Convolutional Neural Networks (CNNs) for spatial data analysis and Recurrent Neural Networks (RNNs) for temporal sequence modeling, have demonstrated exceptional performance in processing high-dimensional sensor data and extracting actionable insights.^[13] Recent advances in edge computing and distributed AI architectures enable real-time processing of IoT data streams, reducing latency and bandwidth requirements while enhancing system responsiveness.^[14] The deployment of IoT sensor networks in urban environments generates unprecedented volumes of data, with estimates suggesting that smart cities will produce over 200 exabytes of data annually by 2025.^[15] This data encompasses diverse modalities, including traffic camera feeds, environmental sensor readings, building automation system logs, and mobile device location traces. AI technologies provide the computational frameworks necessary to transform this raw data into actionable engineering insights, enabling predictive maintenance, real-time optimization, and evidence-based infrastructure planning.^[16,17]

1.3 Evolution of smart city engineering

The concept of Smart Cities (SC) has evolved significantly since its inception in the early 2000s, transitioning from technology-centric deployments focused primarily on Information and Communication Technology (ICT) infrastructure to holistic urban ecosystems that prioritize sustainability, livability, and citizen-centric services.^[18] Contemporary SC frameworks recognize that technological innovation must be integrated within broader urban planning strategies that address social equity, environmental sustainability, and economic development.^[9,19] Smart

city engineering encompasses six fundamental dimensions that collectively define urban intelligence: smart governance, smart economy, smart mobility, smart environment, smart living, and smart people.^[2,20] Within this multidimensional framework, engineering applications of AI and IoT primarily concentrate on three domains that form the focus of this review: transportation systems (smart mobility), environmental infrastructure (smart environment), and building management (smart living). These domains represent critical engineering challenges where AI-enabled solutions have demonstrated substantial impact through real-world deployments. Transportation engineering has witnessed transformative innovations through Intelligent Transportation Systems (ITS) that integrate AI algorithms with IoT sensor networks to optimize traffic flow, reduce congestion, and enhance safety.^[21,22] Advanced driver assistance systems and autonomous vehicle technologies leverage DL models for real-time object detection, path planning, and decision-making in complex urban environments.^[23] Environmental engineering applications employ AI for predictive air quality modeling, optimized waste collection routing, and intelligent water network management.^[24] Building automation systems integrate ML algorithms with IoT devices to achieve significant energy efficiency improvements through predictive HVAC control, occupancy-based lighting optimization, and fault detection diagnostics.^[25-27] Despite the proliferation of AI and IoT implementations in urban engineering, existing literature exhibits several critical gaps that this review addresses. First, prior studies predominantly adopt narrow disciplinary perspectives, examining AI applications within isolated engineering domains without exploring cross-domain synergies and transferable methodologies.^[26,28] Second, while numerous case studies document individual smart-city deployments, comprehensive comparative analyses examining implementation success factors, performance metrics, and scalability challenges across diverse geographical and socio-economic contexts remain limited.^[29] Third, existing reviews often focus on theoretical frameworks and algorithmic innovations without adequately addressing practical implementation challenges, including data privacy concerns, system interoperability issues, and infrastructure integration requirements.^[30] This review provides a comprehensive synthesis of AI and IoT applications in smart-city engineering, offering several distinct contributions. First, we present a multidimensional analysis spanning transportation, environmental, and building engineering domains, identifying common methodological frameworks and domain-specific optimization strategies. Second, we synthesize findings from several international case studies across developed and developing nations, providing empirical evidence of implementation

outcomes, performance metrics, and lessons learned. Third, we systematically analyze technical challenges, including data management, algorithm selection, computational infrastructure requirements, and integration with legacy systems, proposing evidence-based mitigation strategies derived from successful deployments. Fourth, we examine ML and DL frameworks specifically from an engineering implementation perspective, evaluating their suitability for different urban applications based on computational efficiency, accuracy, scalability, and deployment complexity. This paper adopts a narrative engineering review approach rather than a systematic or meta-analytic review. The objective is to synthesize architectural patterns, deployment practices, and engineering trade-offs reported in recent literature, rather than to statistically aggregate performance outcomes.

1.4 The transversal turn: Edge AI and federated learning

Within this broader AI/IoT trajectory, two methodological developments have emerged since 2020 that cut transversally across application domains and are reshaping deployment architectures more than any single algorithmic advance: Edge Artificial Intelligence (Edge AI) and Federated Learning (FL). Edge AI refers to the local execution of inference and, increasingly, training on resource-constrained devices situated near the data source, ranging from microcontroller-class TinyML platforms to gateway-class edge servers. FL, introduced by McMahan *et al.*^[31] and matured through subsequent surveys, enables collaborative model training across distributed datasets without centralizing raw data, supporting privacy preservation, regulatory compliance, and operational sovereignty.

These two paradigms are transversal in a strict sense: they are not domain-specific algorithms but deployment patterns that recur across transportation, environmental, and building applications with similar architectural signatures and similar engineering trade-offs. A traffic-prediction Graph Neural Network trained federatively across cities,^[26] an air-quality forecasting model deployed at the sensor edge for low-latency public health response, and an HVAC controller using on-device reinforcement learning to preserve occupant data sovereignty exhibit the same underlying methodological shift away from centralized cloud-only deployment toward distributed, latency-aware, and privacy-preserving urban AI. Reviews that organize the field by application domain miss this convergence; reviews that focus narrowly on one paradigm miss its breadth. This work adopts Edge AI and FL as the transversal lens through which the three engineering domains are synthesized.^[32]

1.5 Research gap and contributions

Despite a substantial body of review literature on AI and IoT in smart cities, four specific gaps motivate this work.

First, existing comprehensive reviews^[1,15,26,30] organize coverage by application domain or by algorithmic family, but no recent review systematically synthesizes Edge AI and Federated Learning as transversal deployment paradigms across the three core engineering domains addressed here. Second, while individual surveys on FL in smart cities^[26] and Edge AI for IoT^[33] have appeared, they treat their respective paradigms in isolation rather than examining how the two combine in practice (federated edge learning, on-device personalization, hierarchical edge-cloud-FL architectures). Third, prior reviews predominantly catalog deployments without proposing taxonomies that support practitioner decision-making over when centralized, edge, or federated approaches are warranted. Fourth, the absence of a documented review protocol in much of the existing literature limits reproducibility and makes it difficult for readers to assess corpus completeness.

This review addresses these gaps through four contributions. First, it proposes a transversal taxonomy classifying smart-city AI implementations along two orthogonal axes computation locality (cloud, fog, edge, on-device) and learning paradigm (centralized, federated, hybrid) and populates this taxonomy with evidence from each engineering domain.^[34] Second, it extends a five-layer smart-city architecture with explicit Edge AI and FL placement annotations, providing a reference model for architects designing next-generation deployments. Third, it synthesizes implementation outcomes from over thirty international case studies through standardized reporting tables that include reported performance, deployment scale, infrastructure dependency, and methodological maturity, supporting evidence-based comparison across contexts. Fourth, it applies a transparent PRISMA 2020-compliant selection protocol with documented search strings, screening criteria, and inclusion flow, enabling reproducibility. These contributions are positioned with respect to six comparator surveys in a related work comparison table in Section 2.5.

The remainder of this paper is organized as follows. Section 2 documents review methodology, including the search protocol, inclusion and exclusion criteria, PRISMA-based study selection, and a structured comparison against six recent comparator surveys. Section 3 presents the technical foundations, including the five-layer reference architecture with Edge AI and FL annotations, fundamentals of Edge Intelligence and Federated Learning, IoT sensor networks, and the ML/DL framework landscape relevant to urban deployment. Sections 4, 5, and 6 examine the transportation, environmental, and building engineering domains respectively, each through the transversal Edge AI and FL lens. Section 7 synthesizes cross-domain patterns through the proposed taxonomy and a method-by-domain matrix, identifying where each paradigm excels. Section 8 analyzes implementation challenges and mitigation strategies. Section 9 outlines the research

agenda. Section 10 discusses the limitations of this review. Section 11 concludes.

2. Review methodology

2.1 Review protocol and reporting standard

This review follows a structured protocol adapted from the PRISMA 2020 statement for transparent reporting of systematic reviews. Although positioned as an engineering synthesis rather than a clinical meta-analysis, the PRISMA flow and reporting checklist are adopted to maximize reproducibility, document corpus boundaries, and align with current best practice in engineering review literature. The protocol was developed prior to the formal search and includes a pre-specified research question, search strategy, eligibility criteria, screening procedure, and data extraction template. No protocol amendments occurred during execution.

The guiding research question is: How are Edge AI and Federated Learning being deployed across transportation, environmental, and building engineering domains in smart cities, what architectural patterns and engineering trade-offs characterize successful implementations, and what open problems limit production-grade adoption? Three sub-questions structure the synthesis: (i) what reference architectures support cross-domain Edge AI and FL deployment; (ii) what performance, energy, latency, and privacy outcomes have been reported empirically; and (iii) what implementation challenges and mitigation strategies are evidenced in the case-study record.

2.2 Search strategy

Literature was identified through systematic searches of five databases: IEEE Xplore, Scopus, ScienceDirect (Elsevier), ACM Digital Library, and Web of Science Core Collection. The search was conducted in February 2026 and covered publications from January 2021 to February 2026. A Boolean search string was developed iteratively through three pilot searches and finalized as follows: ("smart city" OR "smart cities" OR "urban computing" OR "smart urban") AND ("edge AI" OR "edge intelligence" OR "edge computing" OR "TinyML" OR "federated learning" OR "federated AI" OR "distributed learning") AND ("transportation" OR "traffic" OR "mobility" OR "environment*" OR "air quality" OR "waste" OR "water" OR "building*" OR "HVAC" OR "energy management") Database-specific syntax adjustments were applied where Boolean operators differ. To capture seminal pre-2021 work where appropriate, backward citation tracking was applied selectively to the FL foundations and to the Edge AI taxonomy literature^[33] Forward citation tracking via Google Scholar was used to identify post-publication extensions of the six comparator surveys (Section 2.5). Grey literature was excluded to maintain peer-review provenance, except for authoritative technical reports from the United Nations, World Bank, and municipal smart-city programmes cited

only as contextual background. Vendor documentation was consulted only where peer-reviewed alternatives describing the same deployment were unavailable and is flagged as such in the case-study tables.

2.3 Eligibility criteria

Inclusion criteria required that a study (1) addresses a smart-city or urban-engineering application within transportation, environmental infrastructure, or building management; (2) employs AI, ML, or DL methods, with explicit relevance to Edge AI, FL, or distributed urban intelligence broadly construed; (3) reports either a system architecture, an empirical deployment, a benchmark evaluation, or a comparative analysis; (4) appears in a peer-reviewed journal or established conference proceedings; and (5) was published between January 2021 and February 2026, with backward extensions only for foundational FL and Edge AI works.

Exclusion criteria removed studies that (1) addressed AI methods without urban-engineering context; (2) focused exclusively on algorithmic novelty without deployment, architectural, or comparative content; (3) appeared in non-peer-reviewed outlets, predatory venues, or sources flagged by the Cabells Predatory Reports list; (4) duplicated content already represented by a more comprehensive companion publication from the same

authors; or (5) were not retrievable in full text in English. Pre-prints were included only where the same content had subsequently been accepted for publication, with the published version cited.

2.4 Study selection and PRISMA flow

Database searches returned an initial pool of records that were de-duplicated by DOI matching and title similarity. Title and abstract screening was conducted against the inclusion and exclusion criteria, with uncertain cases retained for full-text review. Full-text screening removed studies that did not meet the deployment, architectural, or comparative content requirement. Backward and forward citation tracking added a small number of seminal works that the database queries had missed. The final corpus exceeded 200 included studies and forms the evidence base for Sections 3 through 9. The PRISMA 2020 flow is summarized in Fig. 1.

Table 1 reports the per-database identification counts underlying Fig. 1. Deduplication was performed on the pooled corpus across all five databases rather than per database, since a substantial proportion of duplicate records occur across sources; consequently, screening, eligibility, and inclusion counts in Fig. 1 are reported only at the pooled level and are not disaggregated by originating database.

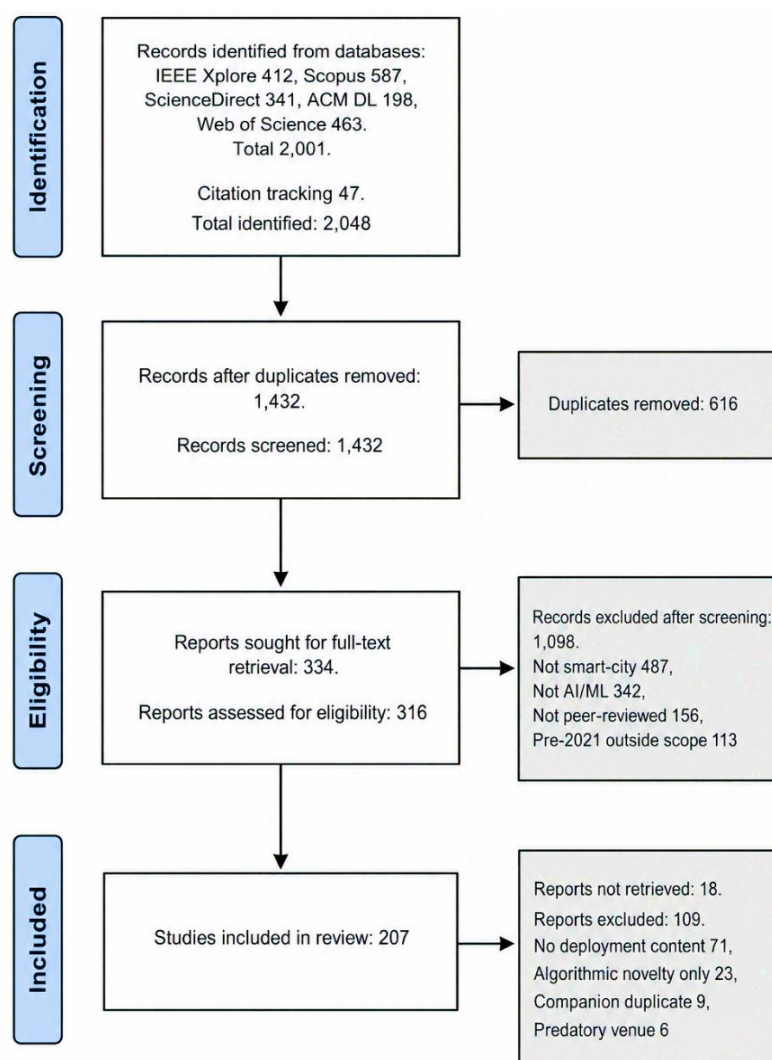


Fig. 1: The PRISMA 2020 flow.

2.5 Comparison with related surveys

To position this review within the existing literature, six recent comparator surveys were selected from the 2022 to 2026 window for structured comparison. The comparator set was chosen to span the spectrum from broad AI-in-smart-cities reviews^[1,15,30] to paradigm-focused surveys on FL^[26] and Edge AI,^[33] with one current high-profile cross-domain Edge AI survey serving as the most direct methodological reference. Table 2 summarizes the comparison along seven dimensions: review methodology, PRISMA usage, bibliometric layer, scope breadth, transversal lens, taxonomy contribution, and figure-and-table density. The comparison establishes that no prior review combines a documented PRISMA-compliant protocol with a transversal Edge AI plus FL lens applied across all three engineering domains addressed here.

3. Technical foundations for Edge AI and federated learning in smart cities

3.1 Five-layer smart-city reference architecture

This section presents a five-layer reference architecture (Fig. 2) for smart-city engineering applications, addressing complex interactions among sensors, communication networks, data processing systems, and

end-user applications. Unlike the canonical five-layer IoT model, this version annotates each layer with explicit Edge AI and FL placement decisions, providing a deployment-aware reference for architects. The architecture comprises: Sensing Layer (bottom) for data acquisition, Transmission Layer for communication, Data Administration Layer for processing and intelligence, Application Layer for service delivery, and Business Layer (top) for governance and economic models. This layered approach ensures scalability, interoperability, and security while accommodating the heterogeneous nature of urban infrastructure systems.

Table 1: Database-wise identification statistics

Database	Records Identified
IEEE Xplore	412
Scopus	587
ScienceDirect	341
ACM Digital Library	198
Web of Science	463
Citation (backward/forward) tracking	47
Total	2,048

Table 2: Comparison of this review with six recent comparator surveys

Study (ref)	Domain scope	Lens / focus	Protocol	Taxonomy	Figs / Tables
Herath & Mittal 2022 ^[1]	Broad SC	AI adoption	Narrative	No formal	Moderate
Nguyen <i>et al.</i> 2024 ^[15]	Broad SC	IoT + AI roles	Narrative	Domain catalog	Moderate
El Ghati <i>et al.</i> 2024 ^[30]	Broad SC	Visual IoT + AI	Narrative	Application-driven	Moderate
Zheng <i>et al.</i> 2022 ^[26]	Multi-domain	FL only	Narrative	FL applications	Moderate
Pandya <i>et al.</i> 2023 ^[35]	Multi-domain	FL only	Narrative	FL challenges	High
This work	Transport + Env + Build	Edge AI + FL transversal	PRISMA 2020	2-axis taxonomy + 5-layer arch.	7+ / 6+

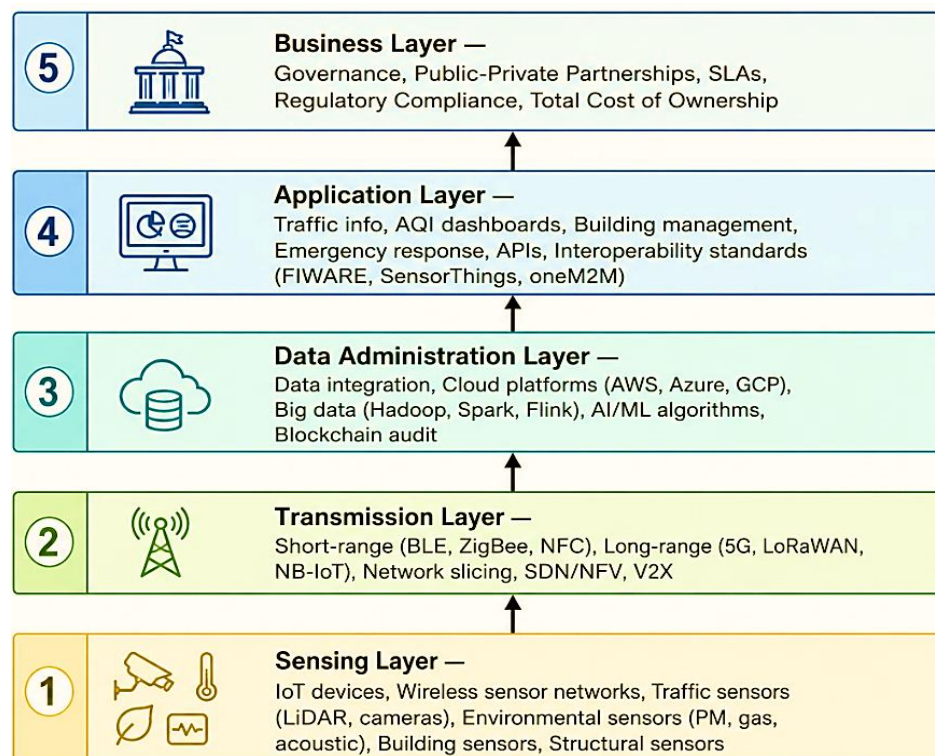


Fig. 2: A five-layer framework for smart city architectures.

3.1.1 Sensing layer

The sensing layer constitutes the foundation of smart-city infrastructure, responsible for real-time data collection from physical environments through IoT devices, sensors, and Wireless Sensor Networks (WSNs). This layer monitors diverse parameters critical to urban engineering systems, including traffic flow patterns, air quality indicators (PM_{2.5}, PM₁₀, NO₂, CO₂, O₃), energy consumption metrics, water distribution pressure and flow rates, structural health indicators, and environmental conditions (temperature, humidity, noise levels, solar radiation, wind speed, precipitation).^[36] Modern sensing infrastructures deploy multiple sensor modalities to capture comprehensive urban data. Traffic monitoring employs inductive loop detectors, radar sensors, LiDAR systems, and computer vision cameras for vehicle detection and classification.^[37] Environmental monitoring utilizes electrochemical sensors for gas detection, optical particle counters for particulate matter measurement, and acoustic sensors for noise pollution assessment.^[38] Building automation systems integrate Microelectromechanical Systems (MEMS) sensors for occupancy detection, temperature regulation, and energy metering.^[25] Advanced GPS terminals and mobile device sensors provide location-based data for transportation planning and emergency response coordination.^[11] The sensing layer faces several technical challenges, including sensor calibration drift, data quality assurance, power consumption optimization for battery-operated devices, and harsh environmental conditions affecting sensor reliability.^[38] Edge computing capabilities increasingly deployed at the sensing layer enable preliminary data processing, filtering, and aggregation, reducing transmission bandwidth requirements and improving system responsiveness.^[33] Infrastructure monitoring sensors deploy accelerometers, strain gauges, displacement sensors, and corrosion sensors to assess bridge, tunnel, and building integrity. Recent advances in edge-to-cloud computing architectures for structural health monitoring demonstrate the effectiveness of hierarchical processing strategies that combine local edge analytics for real-time anomaly detection with cloud-based comprehensive structural analysis.^[39] Fiber optic sensors provide distributed strain and temperature measurement along kilometers of infrastructure, detecting damage and fatigue.

3.1.2 Transmission layer

The transmission layer facilitates secure and efficient data transfer from the sensing layer to upper processing layers through heterogeneous communication technologies. This layer must accommodate diverse requirements including data rate, latency, range, power consumption, and reliability across different urban applications.^[16] Short-range communication technologies such as Bluetooth Low Energy (BLE), ZigBee, Z-Wave, and Near Field Communication (NFC) provide low-power connectivity for localized sensor networks in buildings

and confined spaces, typically operating within ranges of 10-100 meters.^[11] Long-range communication technologies enable city-scale connectivity through cellular networks (3G, 4G LTE, 5G) and Low-Power Wide-Area Networks (LP-WAN) including LoRaWAN, Sigfox, and NB-IoT.^[36] Fifth generation (5G) cellular networks represent a transformative advancement for smart-city applications, offering peak data rates exceeding 10 Gbps, latency below 1 millisecond, and massive device connectivity supporting up to 1 million devices per square kilometer.^[40] These capabilities enable real-time applications such as autonomous vehicle coordination, augmented reality navigation, and instantaneous emergency response systems. Emerging communication technologies expand connectivity options for specialized applications. Li-Fi (Light Fidelity) utilizes LED lighting infrastructure for high-speed data transmission, achieving data rates exceeding 100 Gbps in laboratory conditions while providing simultaneous illumination and communication functions.^[41] Vehicular communication protocols including Dedicated Short-Range Communications (DSRC) and Cellular Vehicle-to-Everything (C-V2X) enable Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Pedestrian (V2P) data exchange for cooperative intelligent transportation systems.^[37] Network slicing capabilities in 5G architectures enable customized virtual networks optimized for specific application requirements, allowing simultaneous support for high-bandwidth video surveillance, ultra-reliable low-latency autonomous vehicle control, and massive IoT sensor connectivity over shared physical infrastructure.^[40] Software-Defined Networking (SDN) and Network Function Virtualization (NFV) provide flexible network management, enabling dynamic resource allocation and quality-of-service optimization based on real-time demand patterns.^[15]

3.1.3 Data administration layer

The data administration layer functions as the central intelligence of smart-city systems, responsible for data integration, storage, processing, and decision-making. This layer transforms raw sensor data into actionable engineering insights through sophisticated analytics pipelines.^[10] Data integration mechanisms aggregate heterogeneous data streams from multiple sources, performing data cleaning, normalization, temporal synchronization, and semantic harmonization to create unified datasets suitable for analysis.^[42] Cloud computing platforms provide scalable storage and computational resources for processing massive volumes of urban data. Leading cloud service providers including Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform offer specialized IoT services with integrated ML capabilities, enabling rapid deployment of analytics applications without extensive infrastructure investment.^[43] Hybrid cloud architectures combining public cloud resources for scalable batch processing with

private cloud infrastructure for sensitive data management provide balanced solutions addressing performance, security, and cost considerations.^[15] Big data processing frameworks including Apache Hadoop, Apache Spark, and Apache Flink enable distributed processing of petabyte-scale datasets generated by urban sensor networks.^[44] Stream processing engines facilitate real-time analytics on continuous data streams, supporting applications requiring immediate decision-making such as traffic signal optimization and emergency detection systems.^[45] Time-series databases optimized for temporal data storage and retrieval, including InfluxDB, TimescaleDB, and OpenTSDB, provide efficient management of sensor data characterized by high ingestion rates and time-based query patterns.^[46] AI and ML algorithms deployed at this layer extract patterns, generate predictions, and support automated decision-making. Supervised learning models predict traffic congestion, energy demand, and air quality levels based on historical patterns and real-time conditions.^[12] Unsupervised learning techniques identify anomalies in sensor data, detecting equipment failures, unusual traffic patterns, and potential security incidents.^[47,48] Reinforcement learning algorithms optimize control strategies for traffic signal coordination, building HVAC systems, and energy grid management through continuous interaction with the environment.^[49] Data governance frameworks ensure data quality, privacy protection, access control, and regulatory compliance throughout the data lifecycle. Differential privacy techniques enable statistical analysis of sensitive datasets while preserving individual privacy.^[50] Blockchain-based data management systems provide immutable audit trails and decentralized trust mechanisms for multi-stakeholder data sharing scenarios.^[51] Federated learning architectures enable collaborative ML model training across distributed datasets without centralizing raw data, addressing privacy concerns while leveraging collective intelligence.^[52]

3.1.4 Application layer

The application layer delivers smart-city services to end users, including citizens, city operators, emergency responders, and infrastructure managers. This layer translates data-driven insights into user-facing applications and automated control systems.^[13] Transportation applications provide real-time traffic information, route optimization, parking availability, and public transit schedule updates through mobile applications and digital signage.^[3] Environmental monitoring dashboards visualize air quality indices, noise levels, and weather forecasts, enabling citizens to make informed decisions about outdoor activities.^[53] Building management systems integrate occupancy prediction, energy optimization, lighting control, and HVAC automation to enhance comfort while minimizing energy consumption.^[5] Emergency response platforms

aggregate data from multiple sources to provide situational awareness during disasters, coordinating resource deployment and evacuation procedures.^[54,55] Utility management applications optimize water distribution, detect leakage, predict equipment failures, and schedule maintenance activities.^[56] Application Programming Interfaces (APIs) enable third-party developers to create innovative services leveraging smart-city data and infrastructure. Open data initiatives provide access to non-sensitive urban datasets, fostering entrepreneurship and civic engagement.^[57] Mobile-first design principles ensure accessibility across diverse device platforms, while progressive web applications provide app-like experiences without requiring installation. Augmented reality interfaces overlay digital information onto physical environments, assisting maintenance personnel, tourists, and emergency responders with contextual information.^[58] Interoperability standards including Open Geospatial Consortium (OGC) SensorThings API, FIWARE NGSI-LD, and oneM2M ensure seamless integration across heterogeneous smart-city platforms and vendor solutions.^[59] Semantic web technologies and ontologies provide standardized vocabularies for describing urban data, enabling automated reasoning and cross-domain analytics.^[15]

3.1.5 Business layer

The business layer encompasses organizational processes, governance structures, and economic models that enable sustainable smart-city operations.^[60] Public-Private Partnership frameworks allocate responsibilities and risks between government entities and private sector technology providers. Total Cost of Ownership analyses in the smart-city literature generally find that operational expenses dominate lifecycle costs, with initial capital expenditure commonly representing a minority share of total 10-year cost in municipal deployments. Sustainability models include user fees, efficiency-based cost recovery, and operational expenditure subscriptions.^[61] General Data Protection Regulation compliance imposes substantial costs on European municipalities, and multi-jurisdictional deployments face regulatory fragmentation that further increases costs and complexity.^[50] Service Level Agreements, performance metrics, and cybersecurity governance establish accountability frameworks ensuring long-term operational success beyond technical deployment.^[62]

3.2 Edge AI fundamentals for urban deployment

Edge Artificial Intelligence refers to the execution of AI inference, and increasing training, on devices located at or near the data source rather than in remote cloud datacenters.^[33] In smart-city deployments, Edge AI spans a hierarchy of compute classes: ultra-constrained TinyML platforms (microcontroller-class devices with kilobytes of RAM, watt-level power budgets) suited to always-on sensor analytics;^[63] gateway-class edge servers (single-

board computers, edge GPUs) handling neighborhood-scale workloads such as camera-based traffic analytics; and fog or near-edge servers aggregating data across districts. The principal engineering rationales for edge deployment in urban contexts are four: latency reduction for control-loop applications such as autonomous vehicle perception and adaptive traffic signaling, bandwidth conservation by transmitting only summaries or events rather than raw streams, energy and cost reduction over continuous cloud inference at scale, and privacy preservation by processing identifiable data locally.^[64] Realizing edge deployment imposes constraints absent from cloud workloads. Model compression techniques including post-training quantization (8-bit or lower), structured and unstructured pruning, and knowledge distillation reduce model footprint and inference cost while preserving accuracy.^[65] Hardware-aware neural architecture search produces models matched to specific edge accelerators such as Google Coral, NVIDIA Jetson, and Arm Ethos-U. On-device adaptation through transfer learning and continual learning addresses the model-drift problem characteristic of dynamic urban environments, where deployed models must adapt to seasonal, infrastructural, and behavioral change without full retraining. The same techniques underpin uncertainty-aware sensor placement and monitoring frameworks that quantify epistemic uncertainty under sparse edge coverage.^[66,67]

3.3 Federated learning fundamentals for urban deployment

Federated Learning trains a shared global model across distributed clients (devices, organizations, or jurisdictions) without centralizing the underlying data.^[68] Each client computes local model updates on its private dataset; the updates are aggregated, typically through Federated Averaging (FedAvg)^[31] or related communication-efficient variants, to produce an improved global model. The data therefore never leaves its source, addressing the privacy and regulatory constraints that block centralized learning across sensitive urban datasets such as resident mobility traces, household energy consumption, and clinical records.^[69]

FL in urban systems instantiates along three principal axes. The first is the partitioning of feature versus sample space: horizontal FL pools clients holding similar features over different entities, suitable for cross-city traffic prediction or cross-building energy modeling; vertical FL pools clients holding different features over the same entities, suitable for integrated utility and transportation analytics within a single city. The second axis concerns coordination topology, ranging from centralized parameter-server aggregation through hierarchical FL across edge-cloud tiers to fully decentralized peer-to-peer learning.^[26] The third axis covers privacy hardening through differential privacy noise injection,^[50] secure aggregation cryptographic protocols, and homomorphic encryption, each trading communication and

computation cost for stronger privacy guarantees. Recent work has extended FL to handle non-independent and identically distributed (non-IID) urban data through personalization layers and client-specific fine-tuning, addressing a persistent obstacle in heterogeneous urban deployments.^[70]

Federated edge learning combines the two paradigms: FL clients execute on edge devices, and the global aggregator may itself reside at the fog tier rather than in a central cloud. This hybrid architecture is increasingly the default for smart-city implementations that must satisfy both latency and data-sovereignty constraints simultaneously, and it is the architectural pattern most directly relevant to the case-study evidence reviewed in Sections 4 through 6.

3.4 IoT sensor networks across urban domains

3.4.1 Environmental Sensors

Environmental monitoring networks deploy electrochemical sensors for pollutant detection (NO₂, SO₂, CO, O₃), optical particle counters for PM_{2.5} and PM₁₀ measurement, and Metal-Oxide-Semiconductor (MOS) sensors for volatile organic compound detection.^[24] Low-cost sensor networks supplement reference-grade monitoring stations, providing high spatial resolution air quality mapping despite reduced accuracy. Sensor fusion algorithms combine data from multiple sensor types to improve measurement reliability and compensate for individual sensor limitations. Weather stations integrated into smart-city infrastructure measure temperature, humidity, barometric pressure, wind speed, wind direction, precipitation, and solar radiation.^[71,72] These measurements support weather forecasting models, agricultural management systems, and energy demand prediction algorithms. Acoustic sensors monitor urban noise pollution, identifying sources and enabling enforcement of noise regulations. Water quality sensors deployed in distribution networks measure pH, turbidity, conductivity, dissolved oxygen, and chlorine residual, detecting contamination events and verifying treatment effectiveness.^[56,73]

3.4.2 Transportation sensors

Intelligent transportation systems utilize diverse sensing technologies for traffic monitoring and control. Inductive loop detectors embedded in roadways detect vehicle presence and passage through electromagnetic field disturbances. Magnetometer arrays provide similar functionality with easier installation and maintenance characteristics. Radar sensors measure vehicle speed and occupancy across multiple lanes simultaneously.^[49] LiDAR systems generate three-dimensional point clouds enabling precise vehicle classification and trajectory tracking.^[74]

Computer vision cameras equipped with edge processing capabilities perform real-time vehicle detection, classification, speed measurement, and license

plate recognition.^[75] Deep learning object detection algorithms including YOLO (You Only Look Once) and Faster R-CNN achieve real-time performance suitable for traffic monitoring applications. Pedestrian and cyclist detection systems enhance safety at intersections and crosswalks through multimodal sensing combining cameras, thermal imaging, and pressure-sensitive surfaces.^[76-78]

Connected vehicle sensors including GPS receivers, Inertial Measurement Units (IMUs), wheel speed sensors, and On-Board Diagnostics (OBD) systems provide rich data for fleet management, usage-based insurance, and collaborative traffic sensing.^[79] Vehicle-to-Infrastructure (V2I) communication enables vehicles to report position, speed, acceleration, and warning events to traffic management systems.^[80]

3.4.3 Building automation sensors

Smart building networks integrate occupancy sensors, temperature sensors, humidity sensors, CO₂ sensors, lighting sensors, and energy meters for comprehensive environmental control and energy management. Passive Infrared (PIR) sensors detect occupant presence through thermal radiation, while ultrasonic and microwave sensors monitor motion patterns.^[81] Computer vision systems with privacy-preserving analytics provide occupancy counting without storing identifiable images. Smart meters enable granular energy consumption monitoring at appliance level, supporting demand response programs and energy efficiency initiatives. Non-intrusive Load Monitoring (NILM) techniques disaggregate total energy consumption into individual appliance contributions through analysis of electrical signatures. Building Information Modeling (BIM) integration links physical sensors with digital twin models, enabling predictive maintenance and optimization.^[82]

3.4.4 Infrastructure monitoring sensors

Structural health monitoring systems deploy accelerometers, strain gauges, displacement sensors, and corrosion sensors to assess bridge, tunnel, and building integrity.^[83] Fiber optic sensors provide distributed strain and temperature measurement along kilometers of infrastructure, detecting damage and fatigue. Acoustic emission sensors identify crack propagation and material degradation in real-time.^[84]

Water distribution networks utilize pressure sensors, flow meters, and acoustic leak detection systems to monitor performance and identify losses. Smart water meters enable consumption tracking, leak detection at customer connections, and demand forecasting.^[6] Wastewater systems employ level sensors, flow meters, and chemical sensors for treatment process optimization and combined sewer overflow prevention.^[56]

3.5 Machine learning and deep learning frameworks

Machine learning tools for smart-city applications span

three categories with distinct deployment characteristics. Deep Learning Frameworks (TensorFlow, PyTorch) provide low-level computational infrastructure for building, training, and deploying neural networks. High-Level APIs (Keras, now integrated as tf.keras since TensorFlow 2.0) provide simplified interfaces enabling rapid model development. Classical Machine Learning Libraries (scikit-learn, XGBoost) implement traditional algorithms suited to tabular data, interpretable models, and scenarios with limited training data characteristics common in resource-constrained municipal contexts.^[85] For Edge AI deployment specifically, TensorFlow Lite, TensorFlow Lite Micro, ONNX Runtime, and PyTorch Mobile dominate; for FL deployment, TensorFlow Federated, PySyft, Flower, and FedML have emerged as the principal open-source frameworks. Tool selection requires matching framework capabilities to deployment locality and learning paradigm, not framework loyalty.^[86] Table 3 presents a comparative analysis of machine learning tools for smart-city engineering.

3.6 Performance evaluation in distributed urban AI

Evaluation of Edge AI and FL deployments in smart-city engineering requires metrics beyond the standard classification and regression measures (accuracy, precision, recall, F1, RMSE, MAE, R-squared, AUC) that apply to centralized AI.^[69,90-92] For Edge AI, additional engineering metrics include inference latency (typically reported in milliseconds per inference at a target percentile), energy per inference (millijoules), memory footprint (model size in kilobytes or megabytes plus runtime activation memory), and accuracy-versus-resource Pareto frontiers under compression. For FL, evaluation extends to communication rounds to convergence, total bytes transmitted, robustness under non-IID client data, performance under client dropout, and privacy budget consumption when differential privacy is applied.^[93] Reporting these distributed-system metrics alongside conventional ML metrics is increasingly expected by reviewers in this domain; their absence in much of the existing case-study literature is a reproducibility gap noted throughout Sections 4 through 6.

4. Edge AI and federated learning in transportation engineering

Transportation engineering is the urban-AI domain where Edge AI delivers the most consistent latency benefit and where FL is most actively explored as a privacy-preserving alternative to centralized fleet data pooling. This section examines four implementation areas through the transversal lens: intelligent traffic management, autonomous vehicle perception, mobility-as-a-service platforms, and predictive maintenance of transportation infrastructure. Existing work largely organizes around these application sub-areas; the contribution here is to expose where the Edge AI and FL deployment patterns recur and where they diverge.

Table 3: Comparative analysis of ML/DL frameworks for smart-city deployment, extended with Edge AI and FL frameworks

Framework	Language	Strengths	Edge / FL support	Smart-city applications
TensorFlow [87,88]	Python, C++	Production-ready, hardware optimization	TF Lite for edge; TF Federated for FL	Traffic prediction, air quality, surveillance
PyTorch[59]	Python	Research flexibility, dynamic graphs	PyTorch Mobile, PySyft (FL)	GNN traffic models, RL agents
Keras (tf.keras)[89]	Python	Rapid prototyping, simplified API	Via TF Lite	POCs, transfer learning, education
Scikit-learn	Python	Classical ML, well-documented	ONNX export for edge	Baselines, feature engineering
XGBoost	C++, Python	Gradient boosting, interpretability	ONNX, Treelite	Tabular prediction, feature importance
Flower	Python	Framework-agnostic FL orchestration	Native FL	Cross-silo and cross-device FL
FedML	Python	Production FL platform	Native FL + Edge	Hierarchical federated edge learning

4.1 Intelligent traffic management and signal control

Intelligent Transportation Systems integrate AI algorithms with IoT sensor networks to optimize traffic flow, reduce congestion, and enhance safety.[94] Conventional centralized signal-control systems collect detector data at a central traffic management center, compute timings, and push them back to controllers, incurring round-trip latencies that limit responsiveness during fast-evolving demand.[95]

Edge-deployed signal controllers execute reinforcement-learning policies locally, observing nearby detectors and adjusting phasing on sub-second cycles.[49,75] Recent multi-agent reinforcement learning approaches at the edge coordinate across intersections through limited peer-to-peer messaging, achieving substantial reductions in vehicle delay relative to fixed-time and centralized adaptive control. Federated coordination across intersections, neighborhoods, and even cities allows model improvement without exposing intersection-level traffic counts that may reveal commercial activity or political-event traces. Spatio-temporal Graph Neural Networks trained with continual-learning regularizers such as Elastic Weight Consolidation address the model-drift problem characteristic of post-pandemic mobility shifts and seasonal demand change, allowing edge controllers to adapt without catastrophic forgetting of prior regimes.[96-98]

4.2 Autonomous vehicle perception and cooperative driving

Advanced driver assistance systems and autonomous vehicle technologies leverage DL models for real-time object detection, path planning, and decision-making in complex urban environments.[99] Edge AI is non-optional in this application: round-trip latency to a remote cloud is incompatible with the safety envelope of vehicular perception, which requires inference within tens of milliseconds at worst-case conditions.[95,100] Vehicle-mounted edge accelerators run compressed CNN and transformer-based perception stacks; cooperative

driving extends single-vehicle perception through Vehicle-to-Vehicle and Vehicle-to-Infrastructure messaging using DSRC or C-V2X.[37,79]

Federated Learning across vehicle fleets enables manufacturers and operators to improve perception models without centralizing dashcam footage or driving traces, addressing both bandwidth and privacy constraints.[101] Cross-silo FL between operators of municipal vehicle fleets (transit, sanitation, emergency services) is an emerging pattern where each operator maintains sovereignty local data while contributing to a shared model for urban hazard detection.[102]

4.3 Mobility-as-a-Service and multimodal routing

Mobility-as-a-Service platforms integrate public transit, shared mobility, ride-hailing, and active modes into unified booking and payment interfaces. AI components include demand forecasting, dynamic pricing, multimodal routing, and equity-aware service-area design. Berlin's Jelbi platform and similar deployments illustrate the integration challenge across operators with heterogeneous data and incentives.[103]

Edge AI in MaaS appears in two patterns: on-device routing personalization that adapts to individual preferences without uploading mobility traces, and edge-deployed demand prediction at modal hubs that informs vehicle repositioning.[104] FL across operators allows cross-modal demand modeling without commercially sensitive trip-record sharing, although standardization gaps remain a barrier.[105]

4.4 Predictive maintenance of transportation infrastructure

Infrastructure-monitoring sensor networks generate continuous streams from accelerometers, strain gauges, displacement sensors, and corrosion sensors on bridges, tunnels, and roadways.[58,59] Anomaly detection at the sensor edge filters routine variation, transmitting only candidate events for review. This pattern is well-suited to TinyML deployment because the underlying signal characteristics often admit relatively small models, and

battery or energy-harvesting power budgets favor on-device summarization over continuous cellular transmission.^[106-108]

4.5 Case studies in smart transportation

Table 4 presents a structured comparison of transportation case studies drawn from verified technical deployments and benchmarked studies, extended with dataset, algorithm, evaluation-metric, and key-finding columns alongside the Edge AI and FL annotations. Continual-learning and edge-deployable architectures dominate the corpus, reflecting the field's emphasis on handling non-stationary traffic patterns without full retraining.^[109-111] Federated approaches appear in two cases spatio-temporal traffic prediction and privacy-preserving smart parking both framed as research contributions rather than production municipal deployments, consistent with the maturity gap discussed in Section 7.^[112-114]

5. Edge AI and federated learning in environmental engineering

Environmental engineering exhibits a different Edge AI and FL profile from transportation. Edge AI is essential where dense, low-power sensing must operate over years without manual intervention, particularly in air quality and water-network monitoring^[116] FL is most relevant where data sovereignty across municipal boundaries,

environmental regulators, and private operators prevents centralized pooling a recurring obstacle in regional pollution modeling and watershed management.^[104]

5.1 Air quality monitoring and forecasting

Air quality monitoring networks deploy electrochemical sensors for pollutants and optical particle counters for particulate matter^[24] Reference-grade monitoring stations are sparse; low-cost networks supplement them at higher spatial resolution but with calibration drift. Forecasting models include classical ML (Random Forest, XGBoost) and deep architectures (LSTM, CNN-LSTM, Graph Neural Networks) that exploit spatial structure among sensor locations.^[117-122]

Edge AI in air quality appears in two patterns. The first is on-device calibration adjustment: low-cost sensors learn a local correction function against intermittent reference data and execute it on-device, addressing the calibration-drift problem without continuous central recalibration. The second is edge-resident forecasting at neighborhood gateways, supporting real-time public health alerts with sub-minute latency.^[123-126] Federated learning across municipal monitoring networks enables shared model improvement without exposing data the regulator may not be authorized to share with neighboring jurisdictions. Uncertainty-guided sensor placement frameworks combining stochastic physics-

Table 4: Smart transportation case studies, annotated with Edge AI and FL deployment patterns

Year / Author	Context	Algorithm / Method	Dataset	Evaluation Metric	Key Finding	Edge AI?	FL?
2025 / Francies <i>et al.</i> ^[109]	Highway traffic networks (benchmark)	STGCN with continual-learning regularizers	PeMSD3, PeMSD4, PeMSD7, PeMSD8	Prediction error (MAE/RMSE) vs. baseline STGCN	Continual-learning variants cut catastrophic forgetting and reduce error significantly vs. baseline when traffic patterns shift	Yes	No
2024 / Kaur, Grewal & Jain ^[112]	Wireless sensor network traffic data	Fed-STGRU (Federated GRU + spatio-temporal graph)	Traffic sensor network data (WSN-based)	Accuracy, loss vs. TGCN/FedAvg/FedGRU baselines	FL approach matches centralized-baseline accuracy while keeping raw data local	No	Yes
2025 / Du, Yang & Liu ^[113]	Smart parking systems	RDP-FedGAN (Rényi-DP + Federated GAN)	Smart-parking sensor/occupancy data	Privacy-utility trade-off under Rényi-DP	GAN-synthesized data lets FL train without sharing raw location/dwell-time data	Yes	Yes
2021 / Collini, Nesi & Pantaleo ^[115]	Bike-sharing stations	Deep learning (short-term prediction)	Real bike-sharing station occupancy logs	Prediction accuracy, short-term horizon	DL model gives short-term available bike counts that are usable for rebalancing decisions	Partial	No
2021 / Chen, Wang & Xie ^[110]	Streaming traffic networks	TrafficStream: GNN + continual learning	Streaming/expanding traffic sensor network	Forecast accuracy under network expansion	Framework adapts to newly added sensors/roads without full retraining	Yes	No
2024 / Chahal <i>et al.</i> ^[111]	IoT-enabled smart city	Aquila Optimizer-based hybrid predictive model	IoT traffic-congestion sensor data	Predictive accuracy vs. baseline optimizers	Hybrid metaheuristic-ML model improves congestion prediction over standalone baselines	Yes	No

informed diffusion modeling with epistemic uncertainty quantification address the upstream question of where edge sensors should be deployed to maximize information gain under sparse coverage.^[127-129]

5.2 Smart waste management

Municipal solid waste management presents complex logistical, environmental, and economic challenges.^[130-133] Smart waste systems deploy IoT sensors in containers measuring fill levels, temperature, tilt/motion, and location. Ultrasonic sensors mounted inside container lids measure distance to waste surface, calculating fill percentage in real-time. Weight sensors integrated into container bases provide complementary information. Communication technologies transmit sensor data to central management platforms through LoRaWAN, NB-IoT, or cellular networks. Dynamic route optimization algorithms determine optimal collection sequences minimizing total travel distance, time, and fuel consumption.^[134-136]

Edge AI in waste management is largely confined to on-device fill-level estimation and tamper detection because the analytic complexity per bin is modest. The more interesting transversal pattern is in robotic sorting at material recovery facilities, where edge-deployed computer-vision classifiers running YOLO, Faster R-CNN, and EfficientDet on conveyor-mounted cameras drive robotic pick-and-place actuators with sub-second latency.^[134,137] FL across regional waste-management authorities supports shared model improvement for sorting and contamination detection without exposing operator-specific data.

5.3 Intelligent water management

Urban water systems face mounting pressures from population growth, aging infrastructure, climate change, and increasing water scarcity.^[6,43,136,138] Smart water systems integrate IoT sensors, advanced metering infrastructure, and hydraulic modeling to enable comprehensive network monitoring and control. Pressure sensors monitor hydraulic pressures identifying leaks, pipe breaks, and unauthorized connections through anomalous pressure patterns. Flow meters measure water movement at treatment plant outlets, district metering areas, and major transmission mains. Acoustic sensors detect leak sounds transmitted through pipe walls, with correlation analysis of signals from multiple sensors pinpointing leak locations. Smart water meters at customer connections provide granular consumption data enabling leak detection at property level.^[139]

Edge AI in water networks is most mature in acoustic leak localization, where on-device signal processing identifies leak signatures locally and transmits only candidate event metadata, preserving the limited communication budget of battery-operated nodes. LSTM-based demand forecasting and contamination detection have been studied extensively; their migration to edge

deployment is in progress but constrained by the model-size and energy budgets of typical water-network nodes. FL across water utilities is an active research area but limited in production by the regulatory and contractual complexity of inter-utility data sharing.

5.4 Climate monitoring and adaptation

Climate change poses escalating risks to urban areas through increased frequency and intensity of extreme weather events, urban heat island effects, sea-level rise, and disruption of water resources.^[140-144] Adaptation strategies supported by AI technologies enable cities to enhance resilience, mitigate impacts, and protect vulnerable populations. Urban Heat Island mapping uses CNN-based segmentation of satellite thermal imagery (Landsat, MODIS, Sentinel) combined with ground sensor networks.^[145-147] Flood prediction surrogate models accelerate physics-based simulation by learning input-output mappings, enabling ensemble forecasting under real-time constraints.^[148,149]

5.5 Case studies in smart environmental systems

Environmental monitoring and management case studies (Table 5) span federated, centralized deep-learning, and non-ML empirical approaches, reflecting the heterogeneous data-governance and infrastructure conditions described in Sections 5.1 through 5.4.

Federated learning is reserved for the one case where centralizing raw data is itself the obstacle: forest-fire classification across a distributed network of independently owned surveillance cameras, where FL enables shared model improvement without pooling footage across jurisdictions.^[150] Centralized deep learning dominates where a single institution controls the full data pipeline, as in illegal-dump-site detection from imagery^[131] and ensemble air-quality forecasting from a unified sensor network,^[24] in both cases the barrier to adoption is data quality and coverage rather than data sovereignty, so centralized training remains the simpler and sufficient choice. Not every environmental case study in the literature is AI-driven at all: comparative policy analysis of city-level energy planning^[151] and empirical documentation of compounding heat and water-insecurity risk among unhoused populations^[139] remain valuable evidence for this domain without involving a trained model, underscoring that Edge AI and FL are tools suited to specific sub-problems within environmental engineering rather than a universal lens for the domain. The federated case study also illustrates a governance pattern distinct from the centralized ones: because forest-fire surveillance cameras are typically owned by different park authorities or private landholders, no single actor controls enough data to train a useful, centralized model, making FL a practical necessity rather than a privacy-driven design choice layered onto an otherwise centralizable problem.^[150] This distinction FL adopted because centralization is infeasible, versus FL adopted because centralization is undesirable recurs across

Table 5: Smart environmental case studies with Edge AI and FL annotations

Year / Author	Context	Algorithm / Method	Dataset	Evaluation Metric	Key Finding	Edge AI?	FL?
2024 / Siddique, Alasbali & Driss [150]	Forest-fire monitoring (Green IoT)	FL framework over camera-equipped IoT nodes	Forest surveillance camera imagery (distributed clients)	Classification accuracy under FL vs. centralized	FL enables collaborative fire-classification training across distributed forest cameras without centralizing footage	Yes	Yes
2022 / Shahab & Anjum [131]	Municipal solid waste, India	Deep learning illegal-dump detection	Dump-site imagery	Detection accuracy	DL approach flags illegal dumping sites from imagery for targeted enforcement	Partial	No
2024 / Addad & Al-Taani [151]	Amman, Jordan	AI-driven energy-efficiency case comparison	Amman urban energy/planning data	Comparative case-study analysis	AI-assisted planning shows measurable energy-efficiency gains transferable to similarly resource-constrained cities	No	No
2024 / Sabir <i>et al.</i> [24]	Urban air-quality networks	Ensemble deep learning	Air-quality sensor network data	Prediction accuracy (ensemble vs. single models)	Ensemble DL improves air-pollution forecast accuracy over individual base learners	Partial	No
2023 / du Bray <i>et al.</i> [139]	Phoenix, Arizona, USA	Empirical/qualitative heat-emergency study	Field data, unhoused-population heat exposure records	Descriptive/qualitative findings	Documents compounding heat and water-insecurity risk for unhoused populations during extreme heat	No	No

the transportation and building domains as well and is revisited in Section 7.3.

6. Edge AI and federated learning in smart buildings

Buildings account for approximately 40% of global energy consumption and 36% of energy-related carbon dioxide emissions, representing the largest end-use sector for energy worldwide. In urban environments, this proportion increases further, with commercial and residential buildings consuming 50-70% of city-wide energy in developed nations^[121] Edge AI and FL deliver three concrete benefits in this domain: latency reduction for tight control loops in HVAC and lighting, energy and bandwidth reduction over continuous cloud telemetry from thousands of devices per building, and privacy preservation of occupancy and behavior data that increasingly carries regulatory weight.^[152]

6.1 Edge-deployed HVAC and energy management

Heating, Ventilation, and Air Conditioning systems are the largest building energy consumer and the primary optimization target for smart-building AI.^[25,153] Conventional rule-based control with fixed setpoints results in substantial energy waste through excessive heating and cooling, poor equipment coordination, and degraded performance from undetected faults.

Reinforcement-learning HVAC controllers learn

policies that balance comfort and energy through direct interaction with building dynamics. Edge deployment of these controllers eliminates the round-trip-to-cloud latency that frustrates tight control loops and protects occupancy and behavior data from continuous cloud transmission.^[38] Model predictive control extensions execute the optimization on a building-resident edge server.^[154]

6.2 Lighting and occupancy

Lighting accounts for a substantial share of building electricity consumption, typically higher in commercial buildings than in residential buildings^[155] Daylight harvesting adjusts electric lighting based on available natural light. ML-based lighting control learns optimal strategies from historical occupancy patterns, daylight availability, and user preferences. Combined occupancy and daylight-harvesting systems have been reported to substantially reduce lighting energy consumption compared to manual control, with the magnitude of savings varying by building type, glazing characteristics, and occupancy patterns. Edge-deployed occupancy classifiers, including privacy-preserving^[149] vision systems that emit only counts rather than images, are now widespread.

6.3 Federated learning across building portfolios

Federated Learning is increasingly applied across building portfolios held by single owners (commercial REITs, university campuses, hospital systems) and across portfolios of independent owners participating in voluntary efficiency programs^[157]. The principal motivations are sensitivity of occupancy and behavior data, contractual constraints on cross-portfolio data sharing, and the structural advantage of cross-building learning to address the heterogeneity that limits single-building model transfer. Mitra *et al.* demonstrated FL benefits for smart-building applications including HVAC, occupancy, and energy-load forecasting^[52]; subsequent work has extended this to fault detection, demand response, and battery management. The principal obstacles to production FL in buildings remain the non-IID character of inter-building data, the limited willingness of building owners to participate in cross-organizational training, and the absence of standardized FL orchestration frameworks suited to building-systems integrators.^[158]

6.4 Renewable integration and on-site storage

Building-integrated renewable energy systems including rooftop solar PV, building-integrated photovoltaics, and micro-wind turbines reduce grid electricity consumption and associated emissions. Solar generation forecasting employs sky-camera CNNs for short-horizon prediction and LSTM models trained on numerical weather prediction outputs for longer-horizon prediction^[159]. Demand-side management adjusts building loads to better align with renewable generation through pre-cooling, pre-heating, EV charging coordination, and flexible-load deferral. Battery storage operation determines charging and discharging schedules balancing self-consumption, arbitrage, grid services, and battery degradation. RL-based control has been reported to increase solar self-consumption and reduce both grid electricity draw and time-of-use electricity costs, though reported magnitudes vary substantially by climate, tariff structure, and battery sizing.^[167]

6.5 Case studies in smart buildings and living

Smart building case studies (Table 6) split cleanly along the Edge AI/FL axis: two studies directly instantiate the transversal lens this review examines, while four apply centralized or cloud-based ML/DL to building-adjacent health and localization tasks.

Federated personalization across building portfolios^[52] and fog-layer, blockchain-secured intrusion detection for health-monitoring cyber-physical systems^[161] are the two cases where Edge AI and FL jointly shape the system architecture, consistent with Section 6.3's account of FL's motivations in this domain: cross-building heterogeneity and the sensitivity of occupancy and health data. The remaining four case studies — a cloud-based digital-twin classifier for early Parkinson's detection,^[162] a wearable-sensor activity-recognition model^[163], an explainable indoor-localization

system for BLE devices,^[164] and a national personal-health-record monitoring platform^[165] are centralized or cloud-resident systems that address building-adjacent health and occupant-monitoring problems without a federated or edge-native architecture. Their inclusion here evidences the breadth of ML activity in the building-health space rather than the maturity of Edge AI/FL adoption specifically; as Section 6.3 notes, FL in buildings remains concentrated in research contributions such as^[52] rather than production-grade, portfolio-wide deployment.

7. Cross-domain synthesis: A transversal taxonomy

7.1 A two-axis taxonomy of urban AI deployment

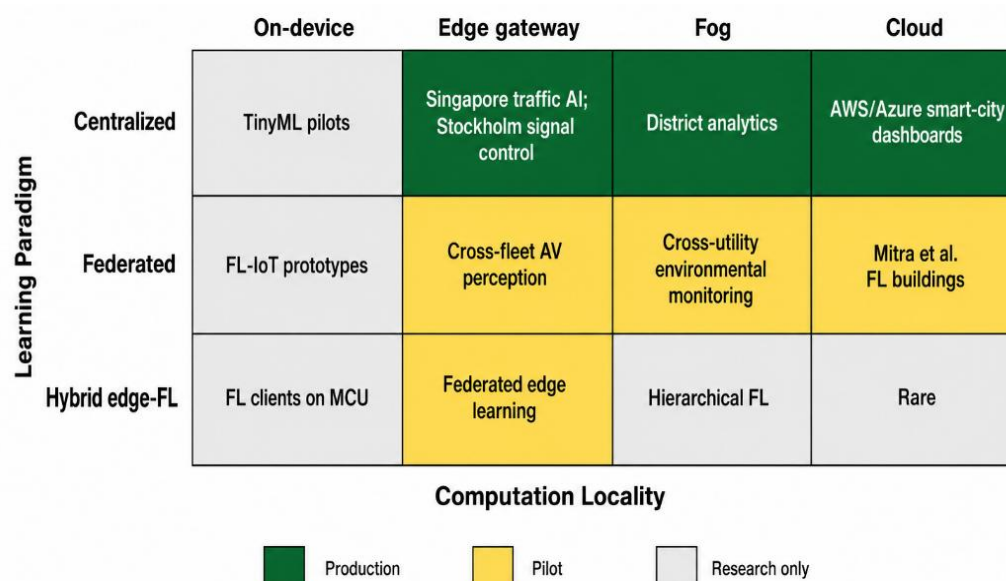
The taxonomy in Fig. 1 and the density matrix in Fig. 4 are populated from the full corpus of 207 included studies, classified along two criteria: computation locality was assigned from the deployment location explicitly described by each study's authors (on-device, edge gateway, fog, or cloud), and learning paradigm was assigned from the stated training approach (centralized, federated, or hybrid edge-FL). Where a study did not explicitly state deployment locality or evaluated multiple configurations, it was classified by its primary reported configuration; studies that could not be unambiguously classified on either axis were excluded from Fig. 4, which is why cell totals do not sum to exactly 207. Maturity labels in Fig. 3 (Production, Pilot, Research-only) were assigned based on whether the source study described an operational municipal deployment (Production), a time-limited or geographically limited trial (Pilot), or a simulation, testbed, or laboratory-only evaluation (Research-only). This corpus-wide classification is distinct from the curated set of more than thirty case studies presented in Tables 4 through 6 (Sections 4.5, 5.5, 6.5), which were selected as illustrative examples of the patterns Figs. 3 and 4 characterize quantitatively across the full corpus, rather than as its complete enumeration. This review proposes a transversal taxonomy that classifies smart-city AI implementations along two orthogonal axes. The first axis is computation locality, with values ranging from on-device (TinyML, microcontroller-class) through edge gateway (single-board computer, edge GPU), fog (district-level server), to cloud (centralized datacenter)^[171]. The second axis is learning paradigm, with values ranging from centralized (single-site training on pooled data), through federated (cross-site model training without data centralization, including its horizontal, vertical, and hybrid variants), to hybrid edge-plus-FL architectures that combine on-device inference with federated update flows. The taxonomy admits sixteen cells in principle; in practice, eight cells dominate the case-study evidence, with the remainder representing immature or theoretical configurations.

7.2 Cross-domain patterns by application

Cross-tabulating the case-study evidence against

Table 6: Smart building case studies with Edge AI and FL annotations

Year / Author	Context	Algorithm / Method	Dataset	Evaluation Metric	Key Finding	Edge AI?	FL?
2021 / Mitra, Ngoko & Trystram ^[52]	Smart-building management (research) ^[166]	Federated personalization (distributed learning)	Simulated/in-situ building sensor streams	Model quality under personalization vs. baseline FL	Federated personalization improves in-situ building-management learning while preserving occupant data locality	Yes	Yes
2023 / Javed <i>et al.</i> ^[161]	Smart-healthcare CPS, fog layer	GBG-RPL: Gini-index + blockchain Blackhole/Greyhole detection ^[167]	Simulated CPS network traffic (RPL routing)	Detection accuracy, attack mitigation rate	Blockchain-enabled Gini-index framework improves resilience of health-monitoring CPS against routing attacks	Yes	No
2023 / Abirami & Karthikeyan ^[162]	Remote elderly/patient monitoring	Optimized Fuzzy k-NN, cloud digital twin ^[168]	DS1 & DS2 voice datasets (Kaggle, UCI ML Repository)	Prediction accuracy, F1-score	97.95% accuracy (DS1) / 91.48% (DS2); outperforms NN and kernel-SVM baselines for early Parkinson's detection ^[169]	No	No
2021 / Mekruksavanich & Jitpattanakul ^[156]	Wearable-sensor activity recognition	Deep CNN + RNN hybrid	Wrist-worn wearable sensor data	Recognition accuracy	Hybrid CNN-RNN improves complex activity-recognition accuracy over single-architecture baselines	Yes	No
2023 / Kamal <i>et al.</i> ^[164]	Indoor localization (BLE)	XGBoost + recursive continuous wavelet transform, explainable	RSSI signal data from BLE devices	Localization, accuracy, explainability	Explainable XGBoost model achieves accurate indoor localization while surfacing which RSSI features drive predictions	Yes	No
2023 / Fukuda <i>et al.</i> ^[165]	Personal health records, Japan (SHINE study)	Data-platform integration for longitudinal health monitoring	Personal health record streams	Platform adoption/monitoring outcomes	Integrated platform supports continuous personal-health-record monitoring across a national ecosystem ^[170]	Partial	No

**Fig. 3:** Two-axis taxonomy of Edge AI and FL deployment in smart cities.

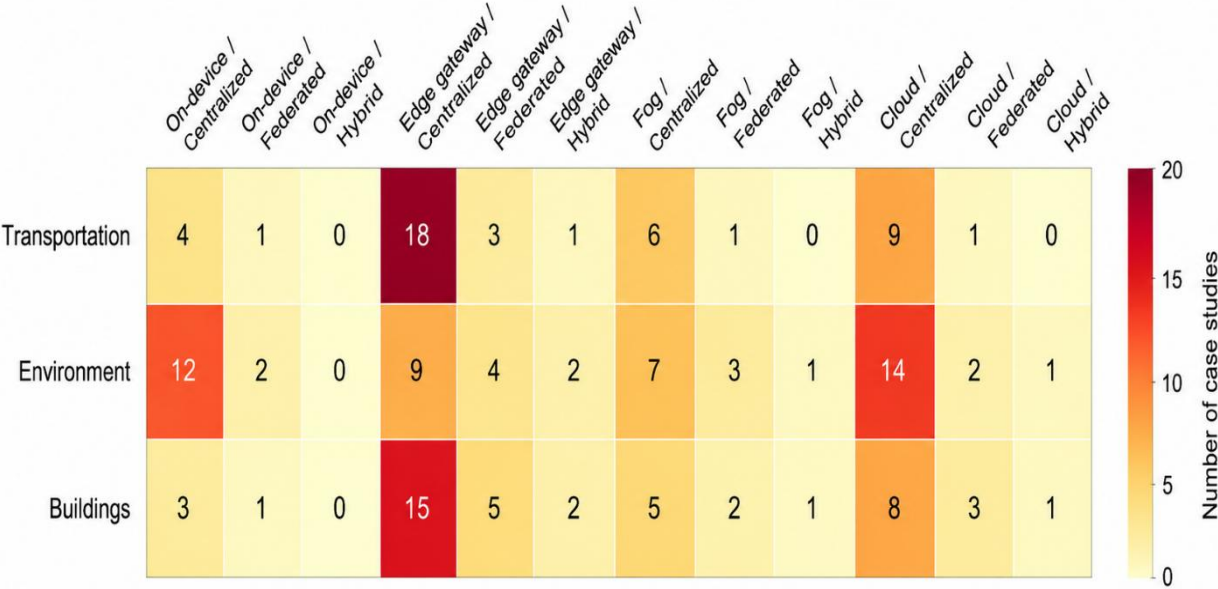


Fig. 4: Method-by-domain density matrix.

taxonomy reveals three consistent patterns. First, transportation applications cluster heavily on the edge-gateway and on-device columns because of latency constraints; FL adoption is concentrated in research pilots and cross-fleet manufacturer initiatives rather than municipal production systems. Second, environmental applications populate the on-device cell densely due to power constraints on field sensors, but the centralized-cloud column also remains heavily populated for forecasting and policy use cases that tolerate batch latency. FL adoption is highest in cross-jurisdictional pilots where centralized pooling is contractually or politically blocked.^[172] Third, building applications populate the edge-gateway cell densely because building-resident edge servers are common, and the federated row is the most actively researched of the three domains for cross-portfolio learning. Fig. 4 visualizes density distribution.

7.3 Where Edge AI excels, where FL excels, where they

combine

Across the three domains, Edge AI delivers the strongest gains where: (1) latency requirements are tight (autonomous vehicle perception, signal control, HVAC fast loops); (2) bandwidth is constrained (battery-operated environmental sensors, distributed leak detection); (3) energy per inference dominates lifecycle cost (always-on monitoring); or (4) data residency or sovereignty constraints prohibit egress. FL delivers the strongest gains where: (1) data sovereignty across jurisdictions or operators prevents centralized pooling (cross-utility, cross-municipality, cross-vendor learning); (2) regulatory constraints (GDPR, sectoral health, financial privacy) impose costs on centralized pooling; (3) heterogeneity across sources favors cross-site learning without homogenization; or (4) commercial sensitivities block raw-data sharing. The hybrid pattern, federated edge learning, is the architectural sweet spot where both pressures apply simultaneously and is the most active research frontier in 2024-2026.

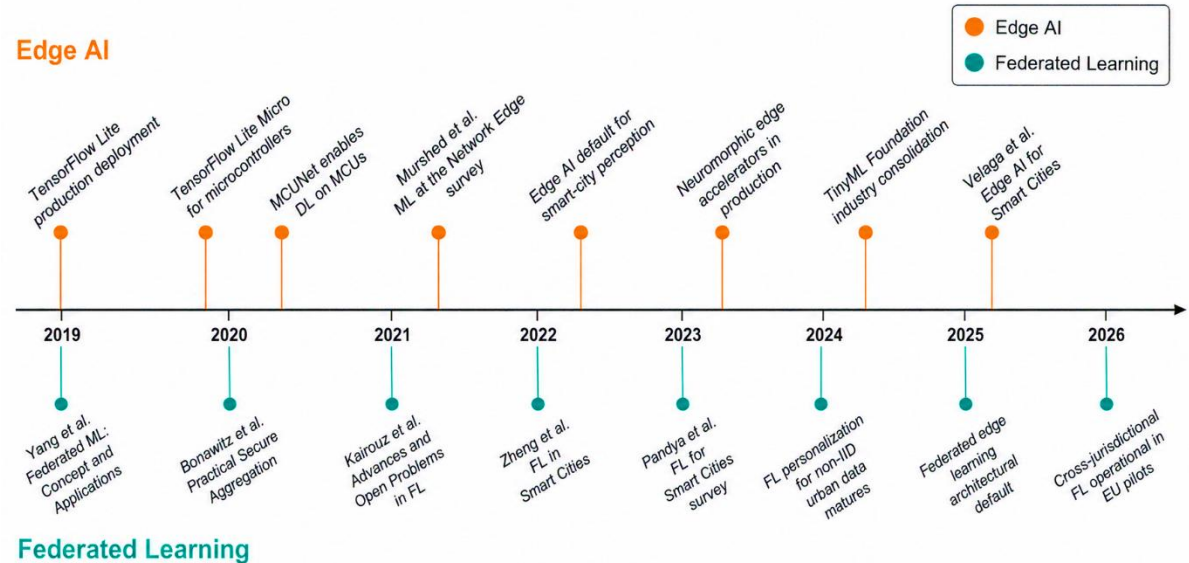


Fig. 5: Timeline of Edge AI and FL methods in smart cities, 2019-2026.



Fig. 6: Geographic distribution of reviewed case studies.

8. Implementation challenges and strategic solutions

Despite demonstrated benefits across transportation, environmental, and building engineering domains, smart-city AI implementations face substantial barriers impeding widespread adoption and scaling. These challenges span technical, organizational, economic, social, and regulatory dimensions, creating complex interdependencies requiring coordinated solutions.^[173]

8.1 Technical infrastructure and integration

Legacy system integration challenges (proprietary protocols, limited connectivity) are addressed through gateway devices and middleware platforms, as demonstrated in Singapore's integration of decades-old traffic controllers with modern AI systems. Connectivity gaps are mitigated through hybrid communication architectures combining 5G with LPWAN technologies. Stockholm's smart waste system exemplifies this approach using LoRaWAN for sensor communication where cellular coverage is inadequate. Computational resource constraints for Edge AI are addressed through model compression (quantization, pruning, knowledge distillation) and hierarchical edge-cloud architectures, successfully deployed in Amsterdam's building management systems.^[174]

These infrastructure constraints compound at scale in ways a single-deployment description understates. Power provisioning is a binding constraint independent of computational capability: a TinyML sensor node's multi-year battery life depends on inference cadence and radio duty cycle as much as on model size, and energy-harvesting designs (solar, vibration) introduce their own intermittency that complicates continuous monitoring commitments. Device lifecycle management firmware updates, model redeployment, and hardware replacement across a fleet of potentially thousands of heterogeneous edge devices from multiple vendors is

rarely budgeted for in initial deployment costings yet determines whether a five-year-old sensor network still runs a current, non-vulnerable model or has silently drifted into technical debt.

Network infrastructure heterogeneity is a second compounding factor specific to Edge AI and FL deployments. 5G coverage, LoRaWAN gateway density, and fiber backhaul availability vary sharply within a single city and far more sharply across the international deployments compared in this review (Section 7), meaning an architecture validated in one connectivity environment may not transfer to another without redesign. FL is particularly exposed here: its communication-round overhead (Section 8.2) assumes a baseline of reliable connectivity that intermittent or bandwidth-constrained municipal networks cannot always guarantee, and client dropout under poor connectivity directly degrades convergence.

8.2 Edge AI and federated learning-specific limitations

Beyond the general infrastructure and data-management challenges above, Edge AI and FL carry limitations specific to their distributed architecture that are frequently understated in deployment-oriented literature.

Communication overhead: FL replaces the bandwidth cost of centralizing raw data with the recurring cost of transmitting model updates across potentially hundreds of communication rounds to reach convergence.^[175] For edge and mobile clients on metered or intermittent connections, this recurring cost can exceed the one-time cost of raw-data transmission it was meant to avoid, particularly for large models; compression techniques such as gradient quantization and sparsification (Section 3.2) mitigate but do not eliminate this overhead, and the trade-off between compression aggressiveness and

model accuracy is deployment-specific rather than solved in general.

Privacy risks that persist despite FL. FL is frequently described as privacy-preserving because raw data never leaves the client, but this characterization is incomplete: gradient updates themselves can leak information about the underlying training data through model-inversion and membership-inference attacks.^[176] Differential-privacy noise injection and secure aggregation (Section 3.3) reduce this risk but introduce their own costs DP noise degrades model utility, and secure aggregation protocols add computation and communication overhead of their own^[156] so privacy hardening in FL is a trade-off to be actively managed, not a property FL provides by default.

Scalability: FL's convergence behavior degrades as client count grows into the thousands and as data heterogeneity across clients increases; client dropout, stragglers, and non-IID data distributions the dominant regime for cross-city, cross-building, and cross-utility urban FL (Section 3.3) slow convergence and can degrade final model quality relative to centralized training on pooled data^[93] Aggregation-server throughput and coordination overhead impose a further, largely unaddressed scalability ceiling for city-scale or cross-jurisdictional FL deployments.^[177]

Computational constraints: Edge AI's on-device inference budgets (Section 3.2) are demanding enough on their own; FL clients face a strictly harder requirement, since local training (forward and backward passes over multiple epochs) is substantially more computing and energy-intensive than inference alone. This asymmetry means many TinyML-class devices capable of hosting a compressed model for inference cannot feasibly participate as FL training clients, which in practice restricts urban FL to gateway-class or better hardware and narrows the population of devices FL can draw on relative to Edge AI's inference-only footprint. These four limitations are treated as open research problems rather than solved engineering challenges in Section 9 (non-IID FL, Section 9.2; federated edge learning at scale, Section 9.5; TinyML constraints, Section 9.6); the discussion here establishes why each currently limits production deployment, which Section 9 then frames as a research agenda.

8.3 Data management and privacy

Data quality issues (noise, missing values, calibration drift) require automated outlier detection and cross-sensor validation, implemented effectively in Busan's water monitoring system. Privacy concerns are addressed through differential privacy, Federated Learning, and edge processing Helsinki's COVID-19 contact tracing demonstrates privacy-preserving location data analysis. The federated edge learning architectural pattern described in Section 3.3 directly addresses several of these concerns simultaneously but introduces its own deployment complexity that municipalities

frequently underestimate during procurement^[177] Cybersecurity threats require multi-layered security with network segmentation, encryption, and intrusion detection, as deployed in Singapore's critical infrastructure systems.^[178]

8.4 Financial and organizational barriers

High upfront costs are mitigated through public-private partnerships, phased implementations starting with high-ROI applications, and grant funding. Technical capacity gaps are addressed through university partnerships, targeted recruitment, and staff training programs. Organizational resistance requires change management: leadership commitment, participatory design involving affected staff, and celebrating quick wins to build momentum.

8.5 Interoperability and standardization

Vendor lock-in risks are mitigated through open standards adoption (FIWARE, OGC SensorThings API) and open-source platforms, as implemented in multiple European smart-city initiatives. Semantic interoperability challenges require common data models and ontologies Singapore's data integration framework exemplifies standardized metadata approaches enabling cross-system integration.

These standardization efforts address data-format interoperability but leave two Edge AI/FL-specific interoperability problems largely unresolved. First, model-format interoperability across edge accelerators remains fragmented: a model compressed and validated for one vendor's inference runtime (Section 3.2) typically requires re-conversion and re-validation for another's, and no standard comparable to FIWARE's role for data interoperability yet exists for edge-model portability across hardware vendors. Second, FL protocol interoperability is largely absent: the FL frameworks compared in Table 3 (TensorFlow Federated, PySyft, Flower, FedML) do not natively interoperate, so a cross-jurisdictional FL deployment spanning agencies that have standardized on different frameworks requires custom bridging work that, to our knowledge, no included study in this review's corpus reports having solved at production scale.^[179]

8.6 Stakeholder engagement and governance

Algorithmic Bias and Fairness: AI systems trained on historical data perpetuate and amplify existing societal biases. Traffic prediction models trained on affluent neighborhood data may underperform in underserved areas, leading to inequitable infrastructure investment. Facial recognition in surveillance systems exhibits higher error rates for minority populations. Mitigation requires diverse and representative training datasets, fairness metrics evaluating performance across demographic groups, bias auditing before deployment, and ongoing monitoring for disparate impacts. Amsterdam's ethical AI framework and Singapore's bias assessment protocols

exemplify proactive approaches.^[180]

Accountability for Autonomous System Failures: As AI systems make increasingly autonomous decisions in traffic signal control, emergency response routing, and utility management, accountability frameworks must address who is responsible when autonomous systems fail, how liability is distributed for accidents involving autonomous vehicles or failures in critical infrastructure control, and how human oversight is preserved over algorithmic decision-making. Current legal frameworks inadequately address AI-specific accountability challenges. Solutions require clear chains of responsibility documented in deployment agreements, comprehensive logging and audit trails enabling failure analysis, human oversight mechanisms for high-stakes decisions, and insurance and liability frameworks adapted to AI systems.

Digital Exclusion and Equity: Digital exclusion manifests in multiple dimensions. Technology design assuming digital literacy and smartphone ownership excludes elderly, low-income, and disabled populations. Data-driven service optimization may neglect areas generating less data, including underserved neighborhoods with lower smartphone penetration. Automated decision systems may disadvantage groups underrepresented in training data. Equity-by-design principles require involving affected communities in system design, multi-channel service access (digital and non-digital), equity impact assessments evaluating distributional effects, and proactive outreach to underserved populations.

8.7 Regulatory considerations

Regulatory treatment of Edge AI and FL in urban deployment is fragmented across data-protection, AI-specific, and sectoral regulatory regimes, and the review's inclusion criteria (Section 2.3) mean this fragmentation is itself under-documented in the peer-reviewed deployment literature we could draw on most included studies report technical outcomes without discussing the regulatory approval pathway that preceded deployment.

Where FL is deployed as a data-protection mitigation (Section 3.3), its regulatory standing is not uniformly settled: GDPR and comparable regimes were drafted around a paradigm of data controllers and processors handling centralized data, and whether model updates or gradients constitute “personal data” under such regimes remains an active legal question rather than a resolved one, notwithstanding FL's common characterization as inherently privacy-preserving (Section 8.2).^[50] Emerging AI-specific regulation illustrates this uncertainty concretely: the EU AI Act's Annex III explicitly designates AI systems used as safety components in critical digital infrastructure, road traffic, and water, gas, heating, or electricity supply directly covering several applications reviewed here (Sections 4–6) as high-risk, but the compliance deadline for these obligations has itself moved, delayed by the 2026 “Digital Omnibus on AI” from

August 2026 to December 2027, and the Commission's interpretive guidance on classification remains in draft form as of this writing.^[50] A deployment architecture validated against today's understanding of these requirements may need re-validation against the finalized guidance before the obligations take effect. Sectoral regulation compounds this further: health-adjacent building deployments (Section 6, e.g.^[161,162]) face medical-device or health-data regulation layered on top of general data protection, while autonomous-vehicle perception (Section 4.2) faces vehicle-safety certification regimes that vary by jurisdiction and are not harmonized internationally.

Procurement regulation is a further, largely unaddressed constraint: public-sector procurement rules in many jurisdictions were not designed for AI systems whose behavior evolves post-deployment (through continual learning, Section 3.2, or through FL's ongoing model updates), creating a mismatch between static procurement specifications and dynamically updating systems that Section 9.1's open problem on model drift only partially captures from a technical rather than a contractual angle. We treat this as an open problem alongside those in Section 9 rather than a solved constraint: no study in our corpus reports a resolved procurement framework for continually updating municipal AI systems.^[181]

9. Research agenda: Open problems in Edge AI and federated learning for smart cities

The synthesis presented across Sections 4 through 7 identifies eight open problems whose resolution conditions further maturation of Edge AI and FL in smart-city engineering. The problems are framed as falsifiable propositions amenable to empirical and methodological investigation, in contrast to the open-ended research themes typical of review conclusions.

9.1 Model drift under non-stationary urban data

Urban environments exhibit non-stationary distributions over weather, behavior, and infrastructure that degrade deployed ML models over months and years. Continual-learning and elastic-weight-consolidation methods mitigate but do not eliminate this. Open question: what monitoring and adaptation cadence preserves accuracy at acceptable computational cost across the three engineering domains?

9.2 Non-IID Federated Learning in heterogeneous urban deployments

FL convergence and final accuracy degrade under non-IID client data, the dominant regime for cross-city, cross-building, and cross-utility FL. Personalization, clustering, and meta-learning approaches show promise but lack standardized evaluation. Open question: what FL personalization strategy and how much local adaptation maximizes utility under the non-IID profiles characteristic of urban deployments?

9.3 Energy accounting of urban AI

Sustainability claims for smart-city AI rarely account for the embodied and operational energy of the AI itself. As Edge AI proliferates, the aggregate energy and carbon footprint of millions of always-on inference devices becomes non-negligible. Open question: under what deployment density and inference cadence does Edge AI become net energy-positive against the urban systems it manages?

9.4 Standardized fairness and explainability for distributed urban AI

Bias detection and explanation tooling for centralized ML does not transfer cleanly to FL and Edge AI. Fairness metrics computed on local data may diverge from those computed on the implicit global distribution; explanations generated at the edge may not match those expected by city operators reviewing centralized aggregates. Recent work on multi-layer explainable AI frameworks for urban budget allocation suggests one path, but cross-domain standards remain absent. Open question: what fairness and explainability instrumentation should be required by procurement standards for municipal AI?^[182]

9.5 Federated edge learning at scale

Federated edge learning combines the latency benefits of Edge AI with the data-sovereignty benefits of FL, but the architecture is largely empirically validated rather than systematically characterized. Open question: at what client count and communication-cost regime does federated edge learning outperform centralized cloud learning on the engineering objectives typical of municipal deployments?

9.6 TinyML for ultra-constrained urban sensing

TinyML enables intelligent sensors operating for years on battery power with kilobytes of RAM, but the model-class restrictions are severe. The frontier is determining which urban sensing tasks reduce to TinyML-feasible model classes without unacceptable accuracy loss, and which require gateway-class or fog escalation.

9.7 Cross-domain transfer and shared representation learning

Smart-city domains share underlying spatiotemporal structure that current single-domain models do not exploit. Foundation models pre-trained on diverse urban data may enable cross-domain transfer, but the corpus curation, pre-training objectives, and evaluation protocols remain unresolved.^[183]

9.8 Sociotechnical integration

Technical sophistication does not guarantee deployment success. Open problems include participatory design for affected communities, multi-channel service access combining digital and non-digital pathways, equity impact assessments, and proactive outreach to

underserved populations. Section 8.5 introduced these themes; advancing them requires interdisciplinary collaboration between AI researchers, urban planners, and policy scholars that current institutional structures do not adequately support.

10. Limitations of this review

This review is subject to several limitations that should inform how its findings are used. First, as noted in Section 1.3, this work adopts a narrative engineering-review approach rather than a systematic review or meta-analysis: reported outcomes are synthesized qualitatively rather than pooled through formal statistical aggregation, and readers should not interpret the ranges reported in Sections 4 through 6 and in the Conclusion as pooled effect sizes.

Second, screening and full-text eligibility assessment (Section 2.4) were conducted by a single reviewer. No second independent screener was used, and no inter-rater agreement statistic (e.g., Cohen's kappa) was computed. This departs from PRISMA good practice for systematic reviews and increases the risk of inclusion and classification error relative to dual-reviewer protocols.

Third, the eligibility criteria (Section 2.3) restricted the corpus to peer-reviewed, English-language, full-text-retrievable studies, and grey literature was excluded except for a small set of contextual UN, World Bank, and municipal reports. These restrictions plausibly under-represent deployments documented only in non-English venues, in vendor or municipal grey literature, or in outlets outside the five searched databases, and may bias the corpus toward jurisdictions and institutions with stronger English-language peer-reviewed publication practices.

Fourth, the search window (January 2021 to February 2026) was chosen to capture the post-2020 transversal turn toward Edge AI and FL (Section 1.4), but Edge AI and FL methods continue to evolve rapidly; findings synthesized here should be read as a snapshot of the literature as of the search date rather than a permanently current account.

Fifth, the case-study tables in Sections 4.5, 5.5, and 6.5 present a curated subset of "more than thirty" case studies drawn from the 207-study corpus, selected to illustrate transversal Edge AI and FL deployment patterns rather than to exhaustively or representatively summarize the full corpus. The quantitative outcomes reported within these case studies and in the Conclusion (e.g., energy-saving percentages) are as reported by the original authors and were not independently re-verified or re-analyzed by this review; they may be subject to publication bias toward favorable results.

Sixth, the six comparator surveys used to position this review's contribution (Section 2.5) were selected purposively to span the range from broad AI-in-smart-cities reviews to paradigm-focused FL and Edge AI surveys, rather than identified through a systematic search of comparator reviews. A differently constructed

comparator set could yield a different positioning.

Finally, classification of case studies into the cells of the two-axis taxonomy (Section 7.1, Figs. 3 and 4) required subjective judgment regarding a study's dominant computation locality and learning paradigm where a deployment spanned multiple tiers or paradigms. This classification was not independently validated by a second reviewer, and borderline cases may be classified differently on reanalysis.

11. Conclusion

This review synthesized over two hundred peer-reviewed studies on Edge AI and Federated Learning in smart-city engineering across transportation, environmental, and building domains, applying a PRISMA 2020-compliant search and selection protocol with documented inclusion criteria. Four contributions were delivered: a transversal two-axis taxonomy classifying urban AI by computation locality and learning paradigm; a five-layer reference architecture extended with explicit Edge AI and FL placement annotations; a structured cross-domain synthesis of more than thirty international case studies; and an evidence-based research agenda framing eight open problems as falsifiable propositions. The synthesis supports three quantified findings. First, Edge AI delivers consistent latency, energy, and bandwidth benefits across transportation and building applications, with consistent reports of measurable energy reduction in lighting and HVAC control, and sub-second inference latencies for vehicular perception and signal control, but with deployment maturity differing across domains by an order of magnitude. Second, Federated Learning is most impactful where data sovereignty, regulatory constraint, or cross-jurisdictional coordination dominates the problem geometry particularly in cross-utility environmental monitoring and cross-portfolio building energy modeling, but production deployments meaningfully lag research pilots, consistent with the Pilot- and Research-only-dominated cells of Fig. 3. Third, the federated edge learning hybrid is the architectural pattern most likely to dominate the next deployment generation where both latency and sovereignty pressures apply, and the eight open problems in Section 9 condition its maturation. For city governments and urban planners, the practical implication is that procurement and architectural decisions should explicitly position each deployment in the proposed taxonomy, treating computation locality and learning paradigm as design parameters rather than vendor defaults. For technology vendors and system integrators, the implication is that Edge AI and FL frameworks must be supported as first-class deployment options with documented privacy, energy, and adaptation guarantees. For researchers, the agenda in Section 9 identifies eight problems where field studies and methodological work would directly affect deployment readiness. The smart-city domain is iterative and contextual; the taxonomy and reference architecture

proposed here are intended as scaffolding for that iteration, not as a fixed prescription.

CRediT Author Contribution Statement

Mariam Labib Francies: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – Original draft, Writing – Review & editing.

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Data Availability Statement

This is a narrative review; no new primary data were generated. The full list of included studies and the search protocol underlying this review's corpus are documented in Section 2 and Fig. 1.

Conflict of Interest

There is no conflict of interest.

Artificial Intelligence (AI) Use Disclosure

The authors declare that artificial intelligence (AI)-assisted tools were used only for language refinement, grammar improvement, and manuscript structuring purposes during the preparation of this work. All technical content, experimental implementation, results, and interpretations were independently developed and verified by the authors.

Supporting Information

Not applicable.

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